Arbitrary Ball Recognition Based on Omni-Directional Vision for Soccer Robots

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Abstract. Recognizing the arbitrary standard FIFA ball is a significant ability for soccer robots to play competition without the constraint of current color-coded environment. This paper describes a novel method to recognize arbitrary FIFA ball based on omni-directional vision system. Firstly the omni-directional vision system and its calibration for distance map are introduced, and the conclusion that the ball on the field can be imaged to be ellipse approximately is derived by analyzing the imaging character. Then the arbitrary FIFA ball is detected by using image processing algorithm to search the ellipse imaged by the ball according to the derivation. In the actual application, a simple but effective ball tracking algorithm is also used to reduce the running time needed after the ball has been recognized globally. The experiment results show that the novel method can recognize the arbitrary FIFA ball effectively and in real-time.

1 Introduction

The RoboCup Middle Size League competition is a standard real-world test bed for autonomous multi-robot control, robot vision and other relative research subjects. It is still a color-coded environment, though some great changes have taken place in the latest competition rules, such as replacing the blue/yellow goals with white goal nets, no color flag post any more. The final goal of RoboCup is that robot soccer team defeats human champion, so robots will have to be able to play competition without the constraint of current color-coded environment. It is a significant step to realize this for soccer robots to be able to recognize any FIFA ball like human being.

Paper [1] [2] [3] proposed a so called Contracting Curve Density (CCD) algorithm to recognize ball without color labeling. This algorithm fits parametric curve models to image data by using local criteria based on local image statistics to separate adjacent regions. This method can extract the contour of ball even in cluttered environments under different illumination, but the vague position of the ball should be known in advance. So the global detection can not be realized by this method. Paper [4] presented a method to detect and track a ball without special color in real-time even in cluttered environments by integrating the Adaboost feature learning algorithm into a condensation tracking framework. Paper [5] presented a novel scheme for fast color invariant ball detection, in which the edged filtered images serve as the input of an

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Adaboost learning procedure that constructs a cascade of classification and regression trees. This method can detect different soccer balls in different environments, but the false positive rate is also high when there are other round objects. So this method is then improved by combining a biologically inspired attention system-VOCUS [6] with the cascade of classifiers. This combination makes the ball recognition highly robust and eliminates the false detection effectively. Paper [7] proposed an edge-based arc fitting algorithm to detect ball for soccer robots. However, above algorithms are all used in perspective camera vision system in which the field of view is far smaller and the image is also far less complex than that of the omni-directional vision system.

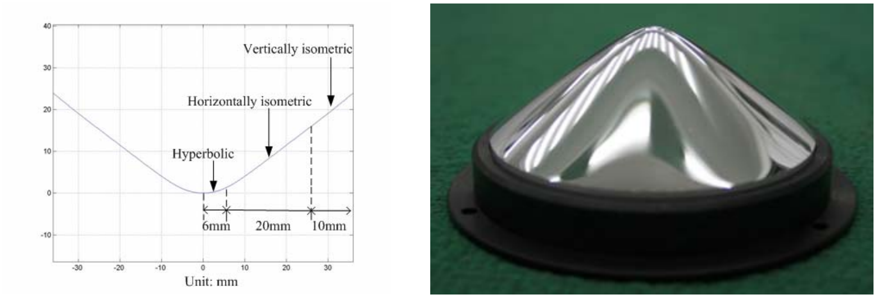
This Paper presents an arbitrary FIFA ball recognition algorithm based on omni-directional vision system for our RoboCup Middle Size League robots-NuBot. In the following part, we will firstly introduce our omni-directional vision system and its calibration for distance map in section 2, and then derive that the ball on the field ground can be imaged to be ellipse approximately and calculate the shape information of the ellipse by analyzing the imaging character in section 3. The image processing algorithm for arbitrary ball recognition will be proposed in section 4. The experiment results and the discussions will be presented in section 5 and section 6 respectively. The conclusion will be given in section 7 finally.

2 Our Omni-Directional Vision System and Its Calibration

The performance of omni-directional vision system is determined almost by the shape of panoramic mirror. It is also the most important factor we have to take into account to calibrate the distance map from the pixel distance of the image coordinate to the metric distance of the real world coordinate at the ground plane.

2.1 The New Panoramic Mirror

We design a new panoramic mirror which is made up of the hyperbolic mirror, the horizontally isometric mirror and the vertically isometric mirror from the inner to the outer. This mirror is different from our former mirror which only includes horizontally isometric mirror and vertically isometric mirror [8]. The only deficiency of our former mirror lies in that the imaging of scene very close to robot is bad, such as the robot itself can not be seen in the panoramic image, which is caused by the difficulty of manufacturing the innermost part of the mirror accurately. So we replace the innermost part of the former mirror with a hyperbolic mirror to solve this problem. The designed profile curve of new mirror and the manufactured mirror are demonstrated in figure 1(a) and figure 1(b). The typical panoramic image captured by our new omni-directional vision system is showed in figure 2(b). Our new omni-directional vision system not only maintains the merit of our former system that is making the imaging resolution of the objects near the robot on the field constant and making the imaging distortion of the objects far from the robot small in vertical direction, but also can have clear imaging of scene very close to robot, such as robot itself.



(a) (b)

Fig. 1. Our new panoramic mirror. (a) The profile curve of the new panoramic mirror. (b) The manufactured panoramic mirror.

2.2 The Calibration for the Distance Map

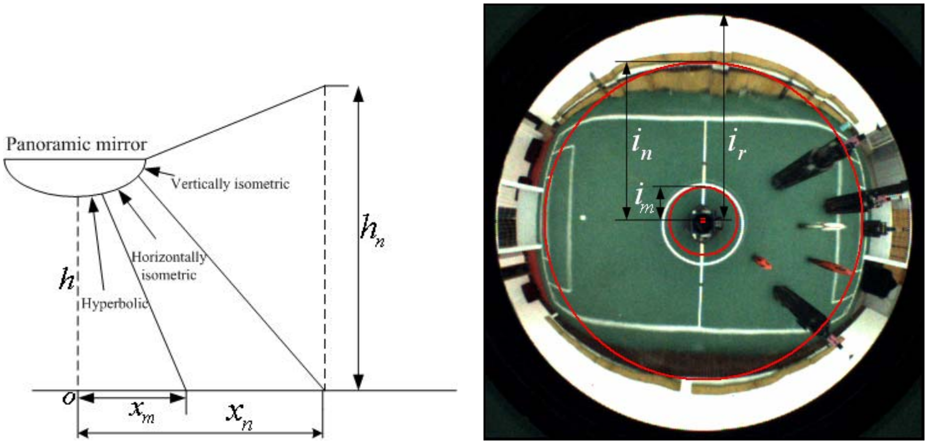
We can calculate the locations of objects in the robot's Cartesian coordinate only when we have calibrated the distance map from the pixel distance of the image coordinate to the metric distance of the real world coordinate at the ground plane. Furthermore, if this calibration has been done, we can analyze what shape the FIFA ball can be imaged in the panoramic image and derive the shape parameters, which is essential for our arbitrary ball recognition method.

We define the center of the mirror equipped by the robot as the center of robot. For the imaging of omni-directional vision is isotropy, the only thing we have to do in the calibration is to calculate the map $x = f(i)$, in which x is the actual distance from some point to the center of robot on the real world ground, and i is the pixel distance from the pixel imaged by the same point to the center of robot on the image.

The three parts of our panoramic mirror are totally different, so we have to calibrate the distance map respectively in three different forms. Firstly we have known the following parameters according to the mirror designing calculation:

- x_m : the maximal distance to the center of robot the hyperbolic part mirror can observe on the real world ground;
- x_n : the maximal distance to the center of robot the horizontally isometric part mirror can observe on the real world ground;
- h_n : the maximal height to the ground the vertically isometric part mirror can observe in the real world location with distance x_n to the center of robot;
- i_m : the pixel distance to the center of robot on the image mapped by x_m ;
- i_n : the pixel distance to the center of robot on the image mapped by x_n ;
- i_r : the pixel distance to the center of robot on the image mapped by h_n , and also equal to the radius of the circle surrounding the virtual part of the image.

Above parameters are shown in figure 2. In figure 2(b), the red point on the center of the image is the imaging point of the center of robot.



(a) (b)

Fig. 2. The parameters of our omni-directional vision system. (a) The sketch of observation range the three part mirrors can observe in real world. (b) The sketch of imaging range of scenes the three part mirrors can observe.

In calibrating the distance map for hyperbolic part mirror, for the hyperbolic mirror is a single viewpoint mirror, we can derive the relationship of the point on the real world ground and the pixel imaged by the point on the panoramic image according the imaging theory of single viewpoint catadioptric vision [9]. We use a lookup table to store the distance map for the hyperbolic part mirror.

In calibrating the distance map for the horizontally isometric part mirror, for the resolution of the imaging of the scenes on the ground is constant, the distance map for this part mirror can be expressed as follows:

$$x = x_m + (i - i_m) * (x_n - x_m) / (i_n - i_m) \tag{1}$$

In calibrating the distance map for the vertically isometric part mirror, for the resolution of the imaging of the scenes vertical to the ground with distance x_n to the center of robot is constant, and the objects on the same incident ray have the same imaging on the panoramic image, as shown in figure 3, the following 2 equations can be derived:

$$(i - i_n) / (i_r - i_n) = h_c / h_n \tag{2}$$

$$h_c / h = (x - x_n) / x \tag{3}$$

So the distance map for the vertically isometric part mirror can be derived with equation (2), (3) as follows:

$$x = (i_r - i_n) * h * x_n / ((i_r - i_n) * h - (i - i_n) * h_n) \tag{4}$$

The distance map function $x = f(i)$ can be expressed as the following piecewise function:

$$x = f(i) = \begin{cases} f_1(i) & \text{if } i \le i_m \\ f_2(i) = x_m + (i - i_m) * (x_n - x_m) / (i_n - i_m) & \text{if } i_m < i \le i_n \\ f_3(i) = (i_r - i_n) * h * x_n / ((i_r - i_n) * h - (i - i_n) * h_n) & \text{if } i_n \le i < i_r \end{cases} \quad (5)$$

In the equation (5), the sub-function $x = f_1(i)$ is replaced with a lookup table in our algorithm.

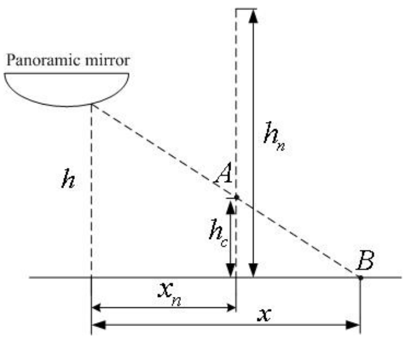


Fig. 3. The sketch of distance map calibration for the vertically isometric part mirror

3 Analysis of the Imaging Character of Ball

In the analysis of the imaging character of ball, we only consider the situation that ball is located on the ground, and we assume that the panoramic mirror is a point with height h to the ground, for the mirror size is far smaller comparing to ball size and the distance from mirror to ball. So the incident rays from ball to mirror can be considered to form a cone tangent to the ball approximately. As we all know, the intersections of a plane and a cone generate conic sections such as circles, ellipses, hyperbolas, parabolas and so on. In this situation, an ellipse is generated by the intersection of the cone and the ground plane, which is shown in figure 4. We define a right hand Cartesian coordinate with the center of robot on the plane as the origin O of the coordinate, with the direction from robot to ball on the plane as x axis. The direction of the major axis of the ellipse coincides with x axis. We assume that the distance between ball and robot is x_b. The imaging of the ball is the same as the imaging of the ellipse in the omni-directional vision system, so we need to derive the shape parameters of the ellipse on the real world ground and then analyze what shape the ellipse is imaged in the panoramic image. The equation of the ellipse is as follows:

$$\frac{(x - x_0)^2}{a^2} + \frac{y^2}{b^2} = 1 \quad (6)$$

In the equation (6), x_0 determines the location of the ellipse, a and b are the semi-major axis and semi-minor axis that determine the shape of the ellipse.

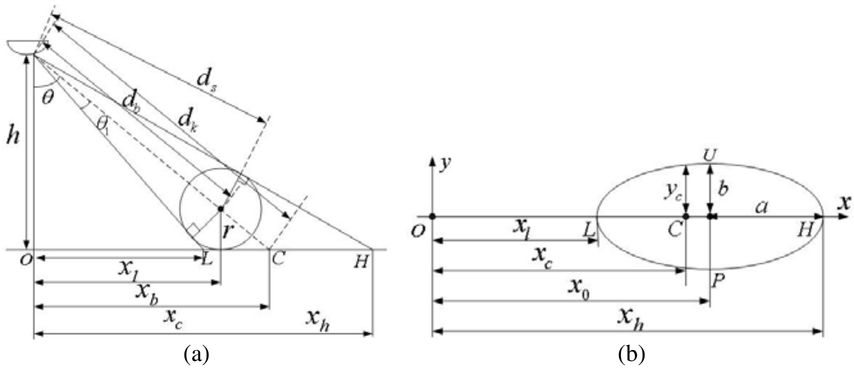


Fig. 4. The sketch of imaging of the ball in omni-directional vision system. (a) The front view of the imaging of the ball. (b) The ellipse generated by the intersection of the cone and the ground plane.

According to figure 4, we get the following equations:

$$x_b = x_c * (h - r) / h \tag{7}$$

$$d_b = \sqrt{(h-r)^2 + x_b^{\,2}} \tag{8}$$

$$d_s = \sqrt{d_b^{\,2} - r^2} \tag{9}$$

$$tg\theta_1 = r / d_s \tag{10}$$

$$tg\theta = x_b / (h - r) \tag{11}$$

$$tg(\theta + \theta_1) = (tg\theta + tg\theta_1) / (1 - tg\theta tg\theta_1) \tag{12}$$

$$tg(\theta - \theta_1) = (tg\theta - tg\theta_1) / (1 + tg\theta tg\theta_1) \tag{13}$$

$$x_l = h * tg(\theta - \theta_1) \tag{14}$$

$$x_h = h * tg(\theta + \theta_1) \tag{15}$$

$$d_k = \sqrt{h^2 + x_c^{\,2}} \tag{16}$$

$$y_c = d_k * tg\theta_1 \tag{17}$$

$$a = (x_h - x_l) / 2 \tag{18}$$

$$x_0 = (x_h + x_l) / 2 \tag{19}$$

The height h of mirror to the ground and the radius r of ball are known in advance. If x_b or x_c is given, we can calculate a and x_0 by substituting the equation (8) ~ (15) into the equation (18) and (19). For the point (x_c , y_c) is located on the ellipse, we can derive the following equation:

$$\frac{(x_c - x_0)^2}{a^2} + \frac{y_c^{\,2}}{b^2} = 1 \tag{20}$$

We can derive b by substituting the equation (7), (16) ~ (19) into the equation (20). For processing the panoramic image to detect the ball, we have to derive further what shape this ellipse will be imaged in the panoramic image. We assume that the ellipse still will be imaged as ellipse, and the distance between the center of the ellipse and the center of robot is i on the panoramic image. Then according to the distance map calibration of our omni-directional vision system in the section 2, we can calculate $x_0 = f(i)$. But it is very complex to calculate a and b if only x_0 is given according to the equation (7) ~ (20), so we do a little simplification on this problem by replacing x_0 with x_c, for the point C is very close to the center of ellipse in figure 4(b). The simplification will be verified to be feasible by the experiment in section 5. So we can calculate $x_c = f(i)$, and then derive the real world ellipse parameters x_l, x_h, x_0, a and b from x_c according to the equation (7) ~ (20). For we have calibrated the distance map in section 2, we can use the inverse function of distance map function to derive the semi-major axis a_i and the semi-minor axis b_i of the imaged ellipse on the panoramic image. The calculation functions are also piecewise functions as follows:

$$a_i = \begin{cases} (f_1^{-1}(x_h) - f_1^{-1}(x_l))/2 & \text{if } x_l < x_h < x_m \\ (f_2^{-1}(x_h) - f_1^{-1}(x_l))/2 & \text{if } x_l < x_m \le x_h < x_n \\ (f_2^{-1}(x_h) - f_2^{-1}(x_l))/2 & \text{if } x_m \le x_l < x_h < x_n \\ (f_3^{-1}(x_h) - f_2^{-1}(x_l))/2 & \text{if } x_l < x_n \le x_h \\ (f_3^{-1}(x_h) - f_3^{-1}(x_l))/2 & \text{if } x_n \le x_l < x_h \end{cases} \tag{21}$$

$$b_i = \begin{cases} b * f_1^{-1}(x_0)/x_0 & \text{if } x_0 < x_m \\ b * f_2^{-1}(x_0)/x_0 & \text{if } x_m \le x_0 < x_n \\ b * f_3^{-1}(x_0)/x_0 & \text{if } x_n < x_0 \end{cases} \tag{22}$$

Up to now, we have finished the derivation on the shape parameters a_i and b_i of the ellipse imaged by the ball on the field ground, given that distance between the center of the ellipse and the center of robot is i on the panoramic image. The process of the calculation can be summarized as follows:

$$i \rightarrow x_c \rightarrow x_l, x_0, x_h, a, b \rightarrow a_i, b_i$$

We store all the values of a_i and b_i varying with i in a lookup table which will be used to detect the arbitrary FIFA ball by image processing in the next section.

4 Image Processing Algorithm for Arbitrary Ball Recognition

We have derived the semi-major axis and the semi-minor axis of the ellipse imaged by the ball on each location of the panoramic image, so we can recognize the arbitrary ball by processing the images to search the possible ellipses according to this character. For the arbitrary FIFA balls have different colors, we can not detect the ball based on color classification as the traditional color objects recognition method. However, the color variations still exist between the pixels belonging to the two sides of the ball contour. So we define two color variation scan methods to detect all of the possible contour points. The first scan method is called rotary scan, in which we define a series of concentric circles with the center of robot on the image as their common centers and we will do the following scan in the concentric circles one by one. In each concentric circle, we search the color variations of every two neighboring pixels, and the color variations are measured by Euclidean distance in YUV color space. If the color variation is higher than a threshold, a possible contour point is found. Then if the distance between every two possible contour points is close to the minor axis value of the ellipse with its center located on this concentric circle, a possible ellipse center point which is the middle point of the two possible contour points is found.

The another scan method is called radial scan, in which we define 360 radial scan rays with the center of robot on the image as their common origins, and we will do the following scan along the radial scan rays one by one. In each radial scan ray, we search the same color variations of every two neighboring pixels as in the rotary scan. If the color variation is higher than a threshold, a possible contour point is found. Then if the distance between every two possible contour points is close to the major axis value of the ellipse with its center located on the middle point of the two possible contour points, a possible ellipse center point which is the middle point is found.

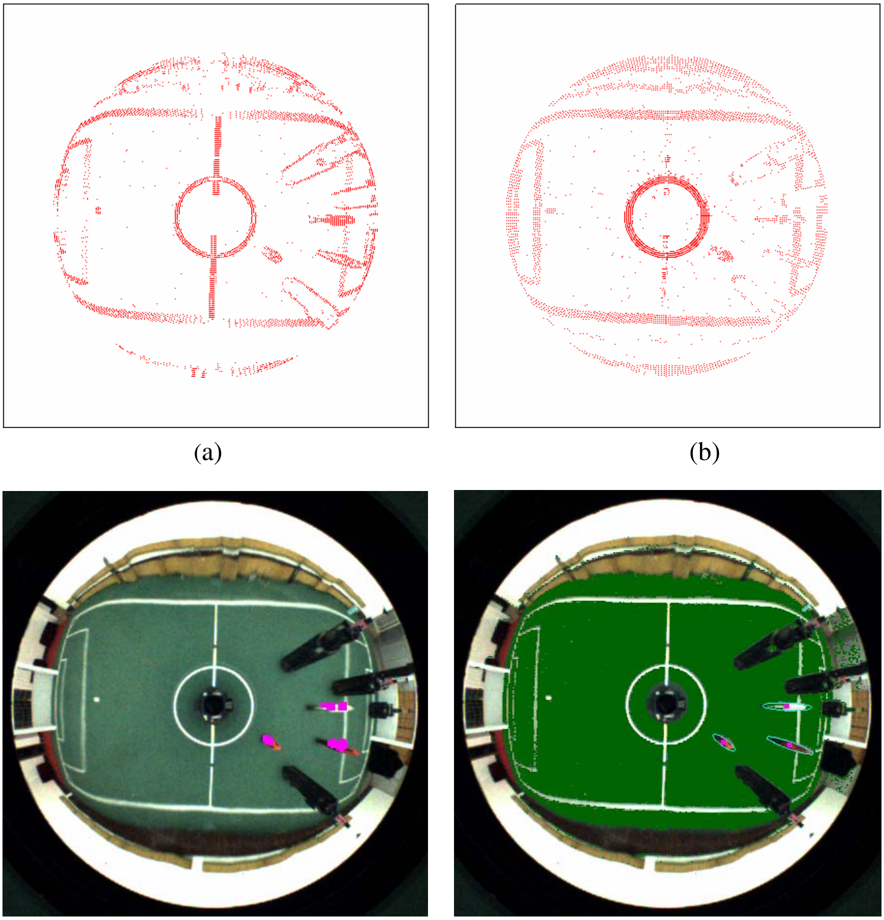
After the two sets of the possible ellipse center points have been acquired by rotary scan and radial scan, we can compare all the points in one set with all the points in the other set one by one. If the two points almost coincide with each other, we can consider that a candidate ellipse exists with the coinciding point as the center of ellipse and also get the equation of this candidate ellipse. Then we match the possible contour points which are detected in the rotary scan and near to the center of the candidate ellipse with the ellipse equation. If enough points match well with the equation, we can verify the candidate ellipse to be real one. Furthermore, for the ball is on the field ground in most situations of the competition, we also combine the traditional image segmentation result based on color classification to reduce the disturbance from outside of the field. After having segmented green field from the image, only those ellipses close to the field are considered to be the final imaging ellipses of the ball.

In the actual application of competition, there will be only one ball needed to recognize on the competition field, so we use the best matching result as the final ball detected. And we also don't need to do above global detection by processing the whole image in every frame. Once the ball is detected globally, we can track the ball by only processing the nearby image area of the ball detected in the last frame with the same image processing algorithm, and the running time needed in the tracking process could be reduced greatly. The nearby image area is dynamically changed with the major-axis and the minor-axis of the ellipse imaged by the ball detected in the last frame. When the ball is lost in the tracking process, the global detection will be restarted.

Up to now, we can recognize a standard FIFA ball without using color classification, so arbitrary standard FIFA balls can be recognized by our method.

5 Experiment Results

Firstly we demonstrate the process and the result of our arbitrary ball recognition algorithm presented in section 4 by processing the typical panoramic image in figure 2(b).



(a) (b) (c) (d)

Fig. 5. The image processing results of our arbitrary ball recognition method. (a) The possible contour points detected by rotary scan. (b) The possible contour points detected by radial scan. (c) The searched candidate ellipse centers. (d) The recognition result of the three arbitrary balls.

The results of the rotary scan and radial scan are shown in figure 5(a), (b) respectively, and the red points in figure 5(a), (b) are the possible contour points. The result of searching the candidate ellipses is demonstrated in figure 5(c) and the center points of the candidate ellipses are denoted as the purple rectangles. The final recognition result is shown in figure 5(d). The recognition result is also verified by combining the image segmentation result based on color classification. The purple rectangles are the center points of the ellipses imaged by the balls on the field ground, the cyan ellipses are the theoretical imaging of the ball on the panoramic image, and the color classification of the green field is also demonstrated in figure 5(d). From figure 5(d) we can find that the three FIFA balls with different colors are all detected correctly.

Table 1. The correct detection rate and the false positives of the arbitrary FIFA ball recognition with different groups of thresholds in image processing algorithm

Different thresholds	The correct detection rate	The false positives
1st group of thresholds	88.34%	7
2nd group of thresholds	89.57%	12
3rd group of thresholds	92.02%	15
4th group of thresholds	94.48%	16
5th group of thresholds	96.32%	17

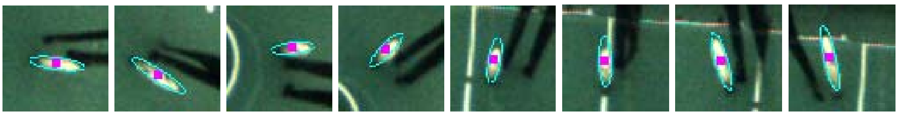


Fig. 6. The results of recognizing and tracking the arbitrary FIFA ball in a test sequence

For doing the statistics of the correct detection rate and the false positives of our recognition method, we collect 55 different panoramic images in which there are 163 standard FIFA balls totally. The adjustment of thresholds in our recognition algorithm especially in matching the possible contour points with the candidate ellipse equation affects the correct detection rate and the false positives. So we process these images with different groups of thresholds and calculate the correct detection rate and the false positives respectively. The correct detection rate and the false positives related to 5 groups of thresholds are demonstrated in table 1. Only global detection is dealt with in our recognition process, and the correct detection rate can be increased greatly by combining our method with object tracking algorithms such as particle filter and other filtering algorithm. So the correct detection rate and the false positives listed in table 1 are acceptable for soccer robots to play competition with arbitrary FIFA ball.

We also test our algorithm in the actual application. Several results of recognizing and tracking the arbitrary ball in a test sequence of panoramic images are demonstrated in figure 6, where only the portion of the images including the detected ball are shown. The video of our robot's recognizing and tracking an arbitrary FIFA ball can be found on our team website: http://www.nubot.com.cn/2008videoen.htm.

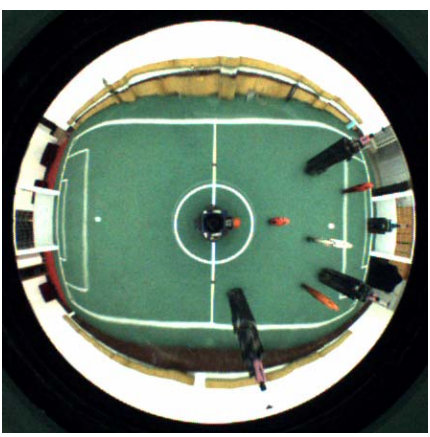
RoboCup Middle Size League competition is a highly dynamic environment and robot must process its sensor information as soon as possible. We also test the running time of our recognition algorithm. It takes about 100ms~150ms to realize global detection by processing a whole panoramic image with dimension 444*442. However, once the ball has been recognized globally, the running time can be reduced to several ms~20ms in the tracking process for only the partial image near the ball detected in the last frame is needed to be processed. So our recognition algorithm can meet the real-time requirement of RoboCup Middle Size League competition.

6 Discussion

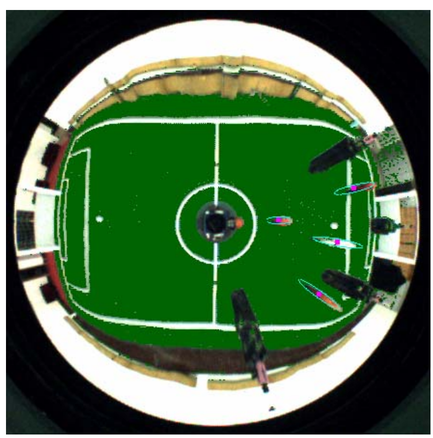
Comparing to the other existing arbitrary ball recognition methods, our algorithm has following good features:

- Our algorithm doesn't need any learning or training process which is necessary in the recognition algorithm based on Adaboost learning;
- Our algorithm can deal with global detection which is not considered in the CCD algorithm;
- Our algorithm is based on omni-directional vision system, the field of view of which is much wider than those perspective cameras used in other existing methods;
- Our algorithm can incorporate the object tracking algorithms easily to detect the arbitrary ball more efficiently and real-time, and the interim and the final results of our algorithm can also be used as important clues for other recognition methods;
- The idea of our algorithm can also be used in any other omni-directional or perspective vision systems, if the imaging character of ball can be analyzed in advance.

However, there are still some deficiencies in our algorithm, which are shown in figure 7. The first deficiency is that the imaging of ball is occluded partly by robot itself when the ball is very close to robot, so our algorithm fails in recognizing this ball. This deficiency can be solved partially by adding the arbitrary ball recognition algorithm based on perspective camera as we had demonstrated successfully in the second free technical challenge of RoboCup2007 Atlanta. In the algorithm, we applied the Sobel filter to detect all the edge points and their gradient directions on the perspective image firstly, and then recognized the arbitrary ball by using Hough transform based on gradient information to detect the circle imaged by the ball. The second deficiency is that the imaging of ball can not be approximated to be ellipse on the image when the ball is imaged by both of the horizontally isometric part mirror and the vertically isometric part mirror partially, so our algorithm matches the ball with bad accuracy, which is shown in the detection result of the ball with maximal distance to robot in figure 7(b). This deficiency may be solved by incorporating other recognition methods such as Adaboost learning algorithm. The third deficiency is that our algorithm only can deal with the situation that the ball is on the field ground. We have to develop some arbitrary ball recognition method based on stereo-vision system to solve this problem.



(a)



(b)

Fig. 7. The recognition results of another panoramic image. (a) The original panoramic image. (b) The arbitrary ball recognition result by our algorithm.

7 Conclusion

In this paper, a novel arbitrary FIFA ball recognition algorithm based on our omni-directional vision system is proposed. Firstly we introduce our omni-directional vision system and its calibration for distance map, and then we derive the conclusion that the ball on the field can be imaged to be ellipse approximately by analyzing the imaging character. We also calculate the major axis and the minor axis of the ellipse on different location of the image in advance. In the image processing, we scan the color variation to search the possible major axis and minor axis of the ellipse by radial scan and rotary scan without color classification, and then we can consider that an ellipse imaged from ball may exist if the middle points of a possible major axis and a possible minor axis are very close to each other on the image. Finally we verify the ball by matching the color variation points searched before near the candidate ellipse center with the ellipse equation. Once the ball has been recognized globally, we also use a simple but effective ball tracking algorithm to reduce the running time needed by only processing the nearby image area of the ball detected in last frame. The experiment results show that our novel method can recognize the arbitrary FIFA ball effectively and in real-time.

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